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# Improved Real-time State-of-Charge Estimation of $\text{LiFePO}_4$ Battery Based on a Novel Thermoelectric Model

Cheng Zhang, Kang Li, *Senior Member, IEEE*, Jing Deng, and Shiji Song

**Abstract**—Li-ion batteries have been widely used in electric vehicles, and battery internal state estimation plays an important role in the battery management system. However, it is technically challenging, in particular, for the estimation of the battery internal temperature and state-of-charge (SOC), which are two key state variables affecting the battery performance. In this paper, a novel method is proposed for real-time simultaneous estimation of these two internal states, thus leading to a significantly improved battery model for real-time SOC estimation. To achieve this, a simplified battery thermoelectric model is firstly built, which couples a thermal submodel and an electrical submodel. The interactions between the battery thermal and electrical behaviours are captured, thus offering a comprehensive description of the battery thermal and electrical behaviour. To achieve more accurate internal state estimations, the model is trained by the simulation error minimization method, and model parameters are optimized by a hybrid optimization method combining a meta-heuristic algorithm and the least square approach. Further, time-varying model parameters under different heat dissipation conditions are considered, and a joint extended Kalman filter is used to simultaneously estimate both the battery internal states and time-varying model parameters in real-time. Experimental results based on the testing data of  $\text{LiFePO}_4$  batteries confirm the efficacy of the proposed method.

**Index Terms**—internal temperature estimation, SOC estimation, thermoelectric model, joint extended Kalman Filter

## I. INTRODUCTION

Electric vehicles (EVs) and hybrid electric vehicles (HEVs) have gained rapid development worldwide in recent years as a means to tackle the pollutions and low efficiency problems of internal combustion engine based vehicles in the transportation sector. The EV and HEV batteries usually consist of hundreds or even thousands of battery cells

connecting in series/parallel configuration. Therefore, a battery management system (BMS) is essential to ensure safe and efficient battery operations [1]. One key functionality of the BMS is to estimate battery internal states that are not directly measurable, such as the battery internal temperature and state of charge (SOC) which are two major factors affecting the battery performance.

In practice, only the surface temperature is directly measurable for commercially used EV batteries. Yet, it is the battery internal temperature that directly affects the battery performance, and a large temperature difference may occur between battery internal and surface temperatures (e.g., sometimes greater than  $10^\circ\text{C}$  [2]), especially in high power demand applications. Real-time estimation of the battery internal temperature is thus of great importance for BMS. Firstly, high internal temperature is a real threat to battery safe operation [1]. Excessive temperature can greatly accelerate the battery ageing process, and even cause fire or explosion of the battery pack in severe cases [3]. The battery internal temperature can reach to a critical temperature a lot quicker than the surface temperature, thus the surface temperature measurement alone is not sufficient to ensure safe battery operation. Secondly, the battery electrical properties, such as usable capacity, internal resistance and power delivery ability all depend on the battery internal temperature. Therefore, it can help develop a more accurate battery electrical model by estimating the battery internal temperature. Finally, the estimation of the battery internal temperature can serve as an indicator in designing proper battery thermal management strategies.

Over the years, various battery thermal models of different accuracy and complexity levels have been proposed, such as complex distributed electrochemical thermal models for thermal simulation [4, 5] and simplified lump-parameter thermal models for real-time applications [6, 7]. Based on the developed models, different model-based estimation methods, such as Kalman filter method, have been proposed for real-time estimation of the battery internal temperature [8, 9].

Battery SOC is another key indicator for EV and HEV batteries. Battery SOC indicates the charge left in the battery available for further service, and it is like the fuel gauge in an ICE car, thus inaccurate SOC estimation may cause the car to strand halfway. Besides, battery SOC can also be used to prevent over-charging and over-discharging operations. There are various SOC estimation methods available in the literature [10–14].

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Despite extensive researches have been carried out, to our knowledge, few papers have dealt with the simultaneous real-time estimation of both the battery internal temperature and SOC, though these two states are closely coupled. Further, for model based battery internal state estimation methods, a battery model needs to be built first. Yet, few papers have considered the interactions between the battery internal thermal and electrical behaviours, except for those complex three dimensional electrochemical models [15, 16]. However, these first-principle electrochemical models are not suitable for real-time EV applications. On the other hand, many papers on battery SOC estimation did consider the effect of the ambient temperature on battery electrical performance [17–19], but only the battery surface temperature is used.

In our previous work [20], the estimation of the battery internal temperature is addressed based on a novel simplified battery thermoelectric model, based on which SOC is then estimated. While the proposed model in [20] has a good model accuracy, but when it is used for the SOC estimation, the results are still poor in some cases. Further, in [20], only heat generation from the series internal resistance is considered, and the model is only applicable for natural heat convection condition at room temperature. The effect of forced heat dissipation methods, which are commonly used in the battery thermal management system, on the battery thermal behaviour is not studied.

The main contributions of this paper are summarized as follows. Firstly, methods for estimating the heat generation rate inside the battery, a key element for building a suitable battery thermal model are investigated and compared. Secondly, time-varying parameters in the thermal model under different heat dissipation conditions are taken into consideration to achieve higher modelling accuracy. Thirdly, a more realistic and detailed battery electrical model that considers both the battery relaxation effect and hysteresis effect is adopted. The battery electrical model is identified under different SOC and temperature levels. With the above introduced techniques, the effect of battery internal temperature and SOC on the battery electrical behaviours is thus captured in detail, offering a comprehensive and better description of the battery thermal and electrical behaviours. Fourthly, to improve the model accuracy, the simulation error minimization method is adopted for training the battery model, and a hybrid optimization method that combines a meta-heuristic algorithm (i.e., the teaching learning based optimization (TLBO) method) and the least square approach is adopted for model parameter optimization. Finally, a joint extended Kalman filter method is applied to estimate the internal model states and time-varying model parameters simultaneously.

The rest of this paper is organized as follows. Section II presents a simplified battery thermoelectric model, including an electrical submodel and a thermal submodel. The test data collected under different heat dissipation scenarios are discussed in Section III. The simulation error minimization model training method and the hybrid parameter optimization method are given in section IV, along with the identified model parameters and modelling results. Considering the time-varying nature of the model parameters, joint EKF method

is applied to estimate the battery internal states and the time-varying model parameters simultaneously in Section V. The experimental results are presented and analysed. Finally, Section VI concludes this paper.

## II. BATTERY THERMOELECTRIC MODEL

### A. Battery electric circuit model

Different kinds of battery models have been developed so far [21]. For the  $\text{LiFePO}_4/\text{C}$  battery used in this paper, to achieve accurate modelling and state estimation, two key challenges must be addressed, i.e., the hysteresis effect and the long relaxation process. In this paper, we adopt a second-order electric circuit model coupled with the hysteresis effect as shown in Fig 1, where  $OCV$  is the battery open circuit

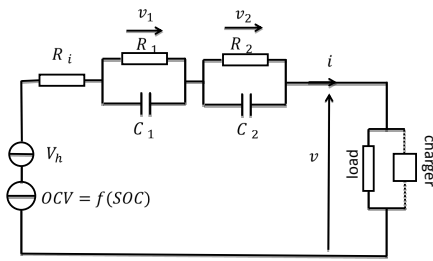


Fig. 1: Battery electric circuit model

voltage ( $OCV$ ),  $v, i$  are the battery terminal voltage and current, respectively.  $R_i$  represents the battery internal resistance.  $R_1C_1$  is used to capture the battery short-term relaxation dynamics, while  $R_2C_2$  for capturing the long-term relaxation process. The over-potentials across these two  $RC$  networks are  $v_1, v_2$ , respectively. Battery  $OCV$  is the battery terminal voltage when the battery internal equilibrium is reached in the absence of load. Battery  $OCV$  depends on the battery SOC, temperature and previous charging/discharging history, which is referred to as the hysteresis effect and is captured by  $V_h$ . However, according to [22], battery  $OCV$  changes slowly with temperature, e.g., less than 10mV as temperature changes from  $-10$  to  $50^\circ\text{C}$ . Therefore, the temperature effect on battery  $OCV$  is not considered here, and

$$OCV = f(soc) \quad (1)$$

Battery SOC can be calculated as follows,

$$soc(k) = soc(k-1) + i(k-1) * T_s / 3600 / C_n \quad (2)$$

where  $T_s$  is the sampling time in seconds, and  $C_n$  is the battery nominal capacity in Ampere hour (Ah).

Following the dynamics of a  $RC$  network, we have

$$v_l(k) = a_l * v_l(k-1) + b_l * i(k-1) \quad (3)$$

where  $a_l = \exp(-T_s / R_l / C_l)$ ,  $b_l = R_l * (1 - a_l)$ ,  $l = 1, 2$ .

The same battery hysteresis dynamic model proposed in [13] is adopted here, as follows,

$$\begin{aligned} V_h(k) &= e^{-\gamma * |i(k-1)|} * V_h(k-1) + \\ & (1 - e^{-\gamma * |i(k-1)|}) * \text{sign}(i(k-1)) * M_h \\ &= c_{k-1} * V_h(k-1) + d_{k-1} * M_h \end{aligned} \quad (4)$$

where  $M_h$  is the maximum hysteresis value, and  $\gamma$  adjusts the changing rate of  $V_h$ .

Combing Eq (1 - 4), the battery electrical submodel can be described as

$$x_e(k) = A_e(k-1) * x_e(k-1) + B_e(k-1) \quad (5)$$

where

$$x_e(k) = [soc(k), v_1(k), v_2(k), V_h(k)]^T$$

and  $A_e = diag([1, a_1, a_2, c_{k-1}])$ ,  $B_e(k-1) = [i(k-1) * T_s/3600/C_n, b_1 * i(k-1), b_2 * i(k-1), d_{k-1} * M_h]^T$

According to Fig 1, battery terminal voltage,  $v(k)$  can be calculated as,

$$v = OCV + V_h + R_i * i + v_1 + v_2 \quad (6)$$

### B. Battery thermal submodel

A battery thermal model consists of two parts: thermal generation and thermal transfer within and outside the battery. Although the heat generation inside the battery is a complex electrochemical process, to build a simplified battery thermal model, three different heat generation calculation methods are widely adopted [6–9, 23], i.e.,

$$\begin{aligned} Q_1 &= R_i * i^2 \\ Q_2 &= i * (v - OCV) \\ Q_3 &= i * (v - OCV) + i * T_{in} * \frac{dOCV}{dT_{in}} \end{aligned} \quad (7)$$

while  $Q_1$  only considers the heat generation over the battery internal resistance  $R_i$ ;  $Q_2$  considers the heat generation caused by the over-potentials such as  $v_1, v_2, V_h$ ;  $Q_3$  further takes into consideration of the heat generation due to entropy change within the battery [9].

Assume that the battery shell temperature and internal temperature are both uniform, and heat generation is uniformly distributed within the battery. Heat conduction is assumed to be the only heat transfer form between the battery internal and shell, and between the battery shell and the ambience.

The resulting simplified battery thermal submodel is given as follows,

$$\begin{aligned} C_{q1} * \frac{dT_{in}}{dt} &= Q_j - k_1 * (T_{in} - T_{sh}), \quad j \in \{1, 2, 3\} \\ C_{q2} * \frac{dT_{sh}}{dt} &= k_1 * (T_{in} - T_{sh}) - k_2 * (T_{sh} - T_{amb}) \end{aligned} \quad (8)$$

where  $T_{in}$  and  $T_{sh}$  are battery internal and shell temperature, respectively;  $T_{amb}$  is the ambient temperature;  $C_{q1}$ ,  $C_{q2}$  are the battery internal and shell thermal capacity, respectively;  $Q_j$  is the heat generation rate;  $k_1$  and  $k_2$  are the heat conduction coefficients between the battery internal and the shell, and between the battery shell and the ambience, respectively.

Eq (8) can be discretized and reformulated as

$$x_t(k) = A_t(k-1) * x_t(k-1) + B_t(k-1) \quad (9)$$

where

$$x_t(k) = [T_{in}(k), T_{sh}(k)]^T$$

$$A_t = \begin{bmatrix} 1 - T_s * k_1 / C_{q1} & T_s * k_1 / C_{q1} \\ T_s * k_1 / C_{q2} & 1 - T_s * (k_1 + k_2) / C_{q2} \end{bmatrix}$$

$$B_t(k-1) = [T_s / C_{q1} * Q_j(k-1), T_s / C_{q2} * k_2 * T_{amb}]^T$$

### C. Coupled thermoelectric model

By combining Eq (5) and (9), the simplified thermoelectric model is given as follows,

$$\begin{aligned} x(k) &= A(k-1) * x(k-1) + B(k-1) \\ v(k) &= f(soc(k)) + V_h(k) + v_1(k) + v_2(k) + R_i * i(k) \end{aligned} \quad (10)$$

where

$$x(k) = [x_e(k); x_t(k)]$$

$$A(k-1) = blkdiag(A_e(k-1), A_t(k-1))$$

$$B(k-1) = [B_e(k-1); B_t(k-1)]$$

Note that  $T_{sh}$  is a model state as well as a model output, since it is directly measurable.

## III. TEST DATA

The test system includes a charger, an electric load and the temperature is controlled by a thermal cabinet, as shown in Fig 2. The Li-ion battery used in this paper is a prismatic LiFePO<sub>4</sub>-Graphite battery purchased from the open market. The battery structure includes the outside shell, i.e., the battery can be made of Aluminium, and the internal layers which can be further divided into three identical sub-cells connected in parallel. Two thermocouples are attached to the battery shell surface, and another thermocouple is inserted into the center area between sub-cell 1 and sub-cell 2. The battery usable capacity and

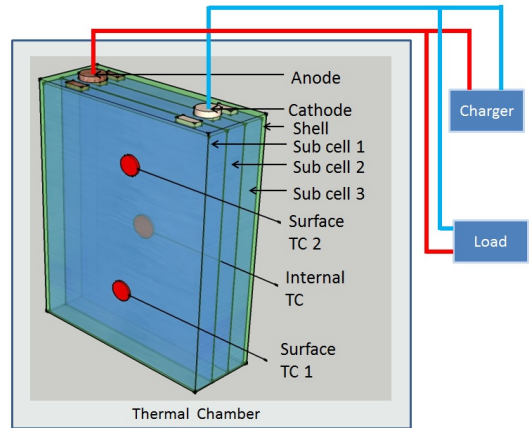


Fig. 2: The battery test system configuration

internal temperature are firstly characterized experimentally at room temperature before and after inserting the thermocouple in order to study whether the inserted thermocouple affects battery performance. The results are shown in Table I, where TC stands for the inserted thermocouple, and 1C and 2C capacity stand for battery usable capacity at 10A and 20A discharging currents. As it can be seen, the effect of the inserted thermocouple on the battery usable capacity (i.e., energy density) and internal resistance (i.e., power density) is negligible. Note that  $R_i$  stands for the series internal resistance which does not vary with SOC. Battery usable capacity usually drops when the load current increases. However, according to Table I, the battery usable capacity increases slightly when the

load current varies from 10A to 20A, which is caused by the higher heat generation rate and thus higher battery temperature when the 20A current is applied.

TABLE I: Battery capacity and Internal resistance test

	1C Capacity (Ah)	2C Capacity (Ah)	$R_i$ (m $\Omega$ )
Before TC	10.460	10.511	13.5
After TC	10.425	10.433	13.5

Then the battery electrical properties are characterized using the standard hybrid pulse power characterization (HPPC) test as shown in Fig 3 under five different ambient temperatures (i.e., [0, 10, 23, 39, 52] $^{\circ}\text{C}$ ). Besides, two fast discharging

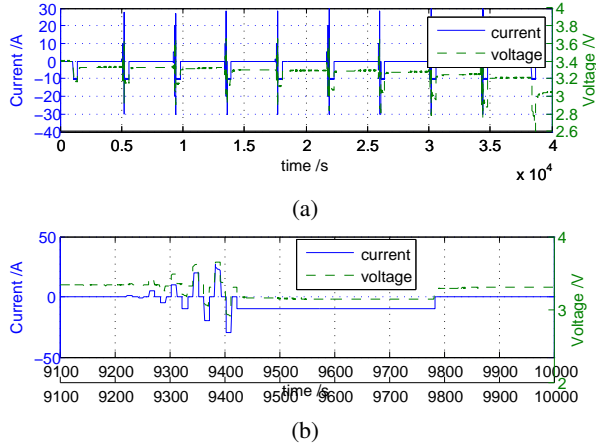


Fig. 3: HPPC discharging test under 23  $^{\circ}\text{C}$ : (a) terminal current and voltage; (b) one zoomed segment

tests are run on the battery under 27 $^{\circ}\text{C}$  ambient temperature, as shown in Fig 4 without forced wind convection and in Fig 5 with forced wind convection, respectively, as a comparison.

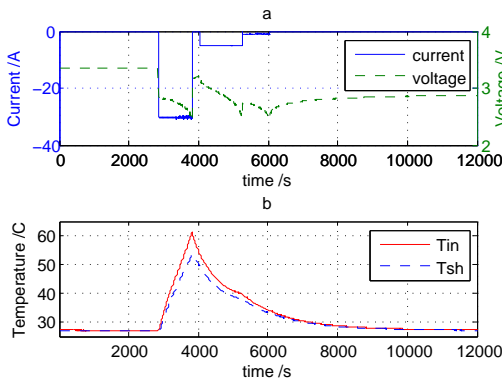


Fig. 4: Battery fast discharging test data without forced wind convection

#### IV. MODEL IDENTIFICATION

##### A. Electric submodel identification

Under laboratory test conditions, battery terminal current and voltage can be accurately measured. Then battery SOC can be calculated by current integration method as in Eq (2).

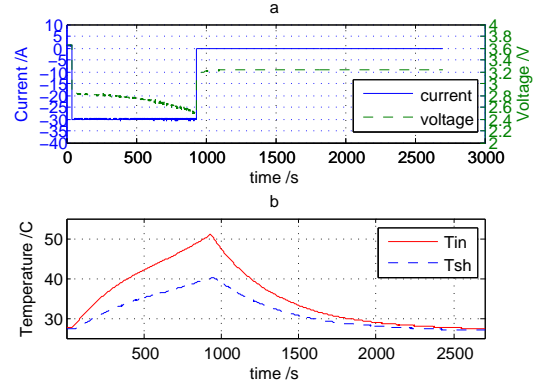


Fig. 5: Battery fast discharging test data with forced wind convection

The same method to determine the battery OCV and hysteresis proposed in [24] is used here. We take the battery voltage after one hour relaxation as the battery charging and discharging OCV, as shown in Fig 6. Their mean value is taken as the battery OCV, and half of the difference between the charging OCV and the discharging OCV is taken as the hysteresis. The other parameters of the electric circuit model

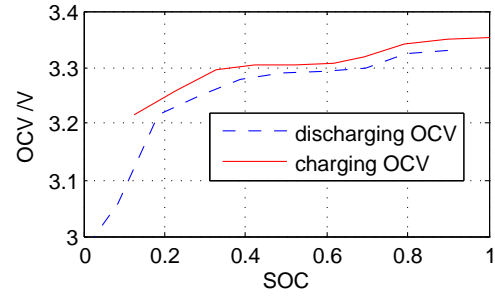


Fig. 6: Battery charging and discharging OCV at 23  $^{\circ}\text{C}$

are identified by fitting the test data. Note that each test data segment (as shown in Fig 3b) is used to identify one set of model parameters at that specific SOC and temperature level. The simulation error minimization method is used in this paper for training the battery electric submodel [25]. To obtain a better model accuracy and stronger consistency, simulation error minimization based model parameter identification methods are preferred over conventional identification methods which minimize the one-step-ahead prediction error in application contexts (e.g., predictive control) where model accuracy is required over a wide horizon [26].

According to Eq (3), the over-potentials across the two  $RC$  networks can be calculated as,

$$v_l(k) = a_l^{k-1} v_l(1) + b_l * \sum_{j=1}^{k-1} a_l^{k-1-j} * i(j), \quad l = 1, 2$$

and  $V_h(k)$  can be calculated using Eq (4) as follows,

$$V_h(k) = \prod_{j=1}^{k-1} c_j * V_h(1) + M_h * \sum_{m=1}^{k-1} d_m * \prod_{j=m+1}^{k-1} c_j$$

Then according to Eq (6), the simulation error is formulated as follows,

$$e(k) = v(k) - f(soc(k)) - V_h(k) - v_1(k) - v_2(k) - R_i * i(k)$$

and the cost function is

$$MSE = \frac{1}{N} \sum_{k=1}^N e^2(k) \quad (11)$$

where  $N$  is the length of the test data.

Note that the parameters in the above model include nonlinear ones, e.g.,  $a_l, \gamma$  and linear ones, e.g.,  $b_l, M_h, R_i$ , and the gradient or Hessian information that are needed for parameter optimization are difficult to calculate. Therefore the hybrid parameter optimization method proposed in [24] is adopted in this paper. The nonlinear parameters are optimized by the TLBO method and linear parameters by the least square method. The least square method is nested in the TLBO procedure to reduce the parameter dimension and improve the convergence speed. The details about the hybrid optimization method can be found in [24].

The identified model parameters are shown in Fig 7. The results reveal that 1)  $R_i$  mainly depends on the battery internal temperature (only slight increases at low SOC); 2)  $R_1, R_2$  depend on both the battery SOC and internal temperature; 3) at low SOC level,  $R_1, R_2$  show a noticeable increase in value; 4) the time constant of the  $R_1C_1$  network,  $\tau_1 = R_1 * C_1$ , depends on the battery SOC. It is clear that, as the temperature increases, the battery internal resistances  $R_i$  and  $R_1, R_2$  decrease. The noticeable increase of  $R_1, R_2$  at very low SOC levels (as shown in Fig 7b) can be verified by the noticeable voltage drop at low SOC levels (as shown in Fig 3a). We can also infer that these varying battery electric parameters will in turn affect the heat generation rate inside the battery based on Eq (7). In summary, the temperature has significant effects on parameters in the battery electric model, which has to be considered in order to improve the modelling and state estimation accuracy.

$M_h, \gamma$  and  $\tau_2 = R_2 * C_2$  are kept constant.  $M_h = 0.02; \gamma = 1.5e - 4; \tau_2 = 600$ .

Then, part of the electric circuit model identification results are shown in Fig 8. The root mean square error (RMSE) at 80% SOC and 10% SOC are about 3 mV and 10 mV, respectively. At a lower SOC level, the battery shows stronger non-linearity, thus higher modelling error occurs.

### B. Thermal submodel identification

The test data shown in Fig 4 (without forced wind convection) is used for thermal model identification. The heat generation results using the three different calculation methods in Eq (7) are compared in Fig 9. The  $dOCV/dT_{in}$  values given in [9] is used here. As can be seen, while  $Q_1$  is noticeably smaller than  $Q_2$  and  $Q_3$ , the difference between  $Q_2$  and  $Q_3$  is not big (mostly less than 10%). Since the temperature effect on the battery OCV is not considered in this paper,  $Q_2$  is adopted as the heat generation inside the battery. Based on the measured  $T_{in}, T_{sh}$ , and the calculated  $Q_2$ , Eq (9) can be identified using the least square method.

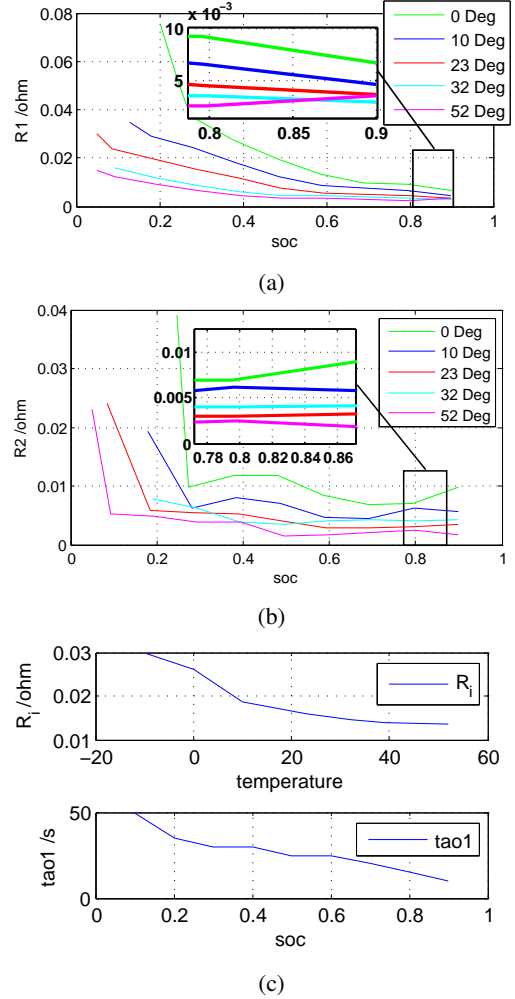


Fig. 7: The electric circuit model parameter identification at different SOC and temperature levels: (a)  $R_1$ ; (b)  $R_2$ ; (c)  $R_i$  and  $\tau_1$

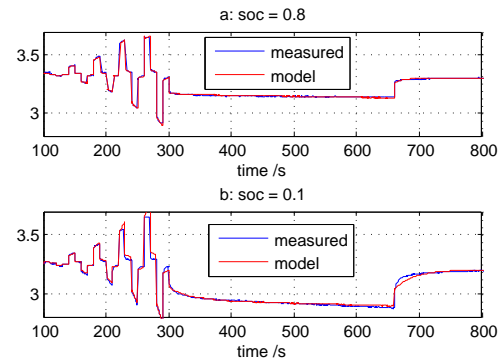


Fig. 8: One part of the electric circuit model identification results at 23 °C: (a) at 80% SOC; (b) at 10% SOC



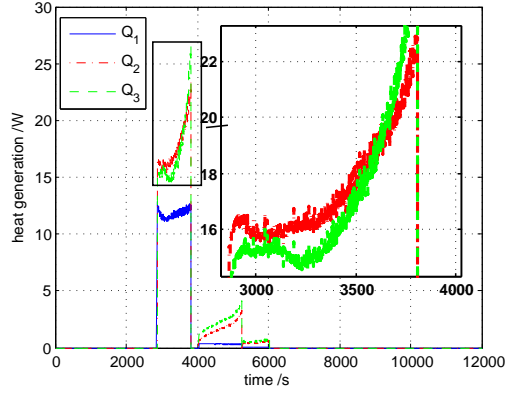


Fig. 9: three different heat generation calculation methods in Eq (7)

Note that while we assume that battery thermal properties  $C_{q1}, k_1, C_{q2}$  are kept constant (according to [27], battery specific heat capacity is independent of SOC and increases slightly with temperature; battery cross-plane thermal conductivity is independent of temperature but depends on SOC.),  $k_2$  certainly depends on the heat dissipation condition, such as cooling wind speed and temperature. According to [23],  $k_2$  also increases with this temperature gradient  $T_{sh} - T_{amb}$ . To take this effect into consideration, two cases are compared here: 1) constant  $k_2$ ; 2) time-varying  $k_2$ , i.e.,  $k_2 = k_{2,1} + k_{2,2} * (T_{sh} - T_{amb})$ .

The thermal modelling results are shown in Fig 10 for constant  $k_2$  and Fig 11 for time-varying  $k_2$ , respectively. The modelling results are summarized in Table II. As shown, when the time-varying nature of  $k_2$  is taken into consideration, the model accuracy is improved noticeably.

Finally, the identified battery thermal model parameters are

$$\begin{aligned} C_{q1} &= 288.77, \quad C_{q2} = 30.8, \\ k_1 &= 1.7312, \quad k_{2,1} = 0.3205, \quad k_{2,2} = 0.0028 \end{aligned} \quad (12)$$

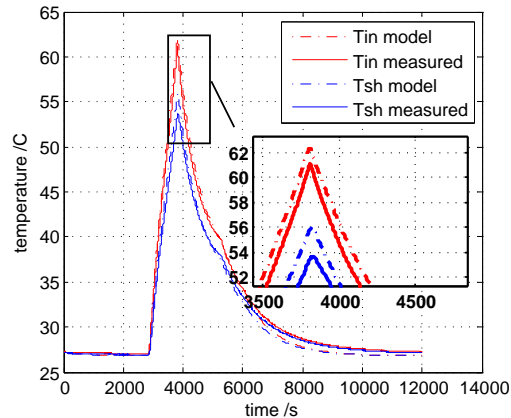


Fig. 10: thermal modelling results with constant  $k_2$

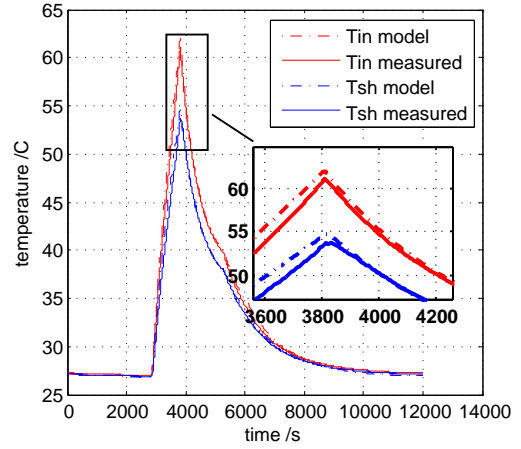


Fig. 11: thermal modelling results with time-varying  $k_2$

TABLE II: Battery thermal submodel identification results

	$T_{in}$ max error	$T_{in}$ RMSE	$T_{sh}$ max error	$T_{sh}$ RMSE
constant $k_2$	1.51	0.695	2.31	0.714
varying $k_2$	0.90	0.469	1.02	0.467

## V. KALMAN FILTER

After the battery model is identified, it can be used for battery internal states estimation. Note that in Eq (10), battery behaviour is described using a state-space equation. Therefore, the popular EKF method can be used for the states estimation.

As discussed above,  $k_2$  depends on the heat dissipation condition. To deal with this, one approach would be to characterize  $k_2$  off-line under different operation conditions and tabulate the results. The tabular can then be used for real-time applications. However, to build such a table requires many running tests which is time consuming. In this paper, an joint EKF is adopted to simultaneously estimate both the model states ( $x$  in Eq (10)) and time-varying model parameter ( $k_2$ ) in realtime [13, 24].

Take  $k_2$  as another model state, and the augmented model state equations become,

$$x_a(k) = A_a(k-1) * x(k-1) + B_a(k-1) \quad (13)$$

where

$$x_a(k) = [x(k); k_2(k)]$$

$$A_a(k-1) = blkdiag(A(k-1), 1)$$

$$B_a(k-1) = [B(k-1); 0]$$

Then  $k_2$  can be estimated along with other model states.

A detailed implementation procedure of the joint EKF method can be found in [13, 24].

The battery fast discharging test data with forced wind convection shown in Fig 5 are used for validation of the proposed internal states estimation method. In order to demonstrate that it is important to consider the couplings between battery thermal and electrical behaviours, two different scenarios are considered and compared, one assuming constant battery model parameters and the other considering the interactions. The system states, i.e.,  $x_a$  in Eq (13) which includes both

electrical states (i.e., battery SOC, over-potentials across RC networks, and hysteresis voltage), and thermal states (i.e., internal temperature and surface temperature), and time-varying model parameter (i.e., heat dissipation level  $k_2$ ), are estimated in both cases.

#### A. Results based on the electrical submodel with constant parameters

The values of the constant parameters in the model are given as follows

$$\tau_1 = 15s; R_1 = 8m\Omega; R_2 = 6m\Omega \quad (14)$$

which are approximated with the corresponding mean values.

The Kalman filter estimation results are shown in Fig 12. It is clear that the estimated battery internal temperature matches well with the measurements during the whole testing period. The maximum error and RMSE of  $T_{in}$  estimation are only about  $1.48^\circ C$  and  $0.44^\circ C$ , respectively. The SOC estimation RMSE is 2.88%.

Since the battery shell temperature is directly measurable, the estimated  $T_{sh}$  results match the measurements perfectly.

The model voltage output is shown in Fig 13, where two short segments with slight bias error can be observed at both the starting and ending stages (around 100s and 900s, respectively). We believe the bias errors are caused by the discrepancy between the adopted constant battery model parameters in Eq (14) and the time-varying true model parameters shown in Fig 7.

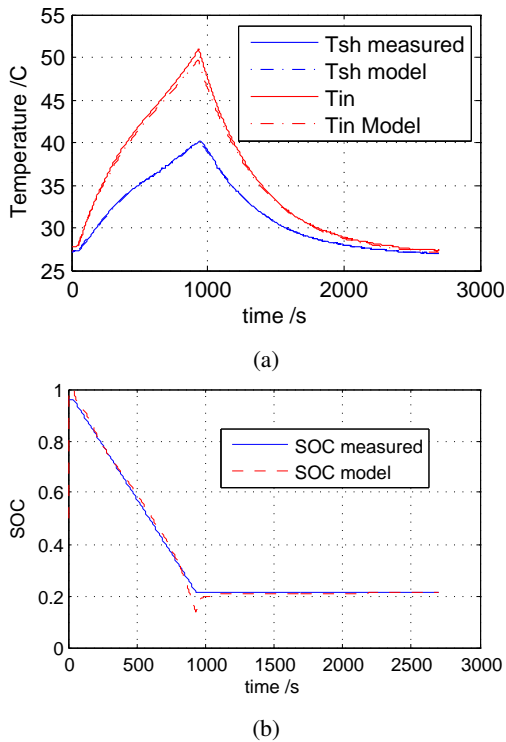


Fig. 12: Kalman filter results assuming constant electrical submodel parameters:  $T_{in}$  and SOC effect (a)  $T_{in}$ ,  $T_{sh}$ ; (b) SOC

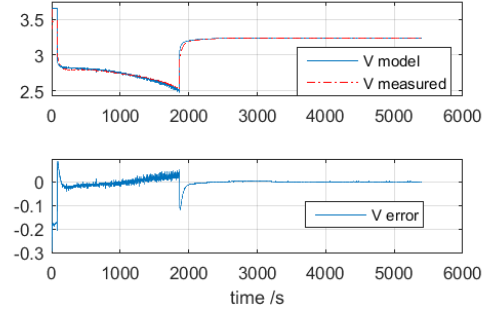


Fig. 13: Kalman filter results assuming constant electrical submodel parameters: battery terminal voltage

#### B. Results considering $T_{in}$ and SOC effects

The Kalman filter results considering  $T_{in}$  and SOC effects are shown in Fig 14. As it is shown, the internal temperature estimation results in Fig 14a are quite similar to Fig 12a. The reason is that in these two scenarios the thermal submodels used are the same. The maximum error and RMSE of  $T_{in}$  estimation are only about  $1.2^\circ C$  and  $0.47^\circ C$ , respectively. These estimation results are comparable with existing results [8, 23, 28], where the RMSE errors lie between 0.5 and  $2^\circ C$ .

The battery SOC estimation results are shown in Fig 14b. As can be seen, the estimated battery SOC converges to the correct value quickly. The SOC estimation RMSE value is 2.31%, about 20% improvement compared with that in Fig 12b. It is evident that the SOC estimation accuracy in Fig 14b is higher than Fig 12b during the whole test period.

The estimation results of the time-varying model parameter  $k_2$  are shown in Fig 14c. The initial value of  $k_2$  is set to be 0.3. As can be seen, the estimated  $k_2$  quickly increased to a much higher value (i.e., 1.3). After the discharging test ended,  $k_2$  converged to a stable value (i.e., 1.2). Comparing this result with Eq (12), we can conclude that the forced wind convection increased  $k_2$  noticeably from less than 0.4 to 1.2. During this test, the electrical submodel parameters change with the battery  $T_{in}$  and SOC, and the results are shown in Fig 15. As can be seen, the value of  $R_1$  started from about  $4m\Omega$  and increased to over  $15m\Omega$ , while the value of  $R_2$  increased from  $4m\Omega$  to about  $7m\Omega$ . Consequently, the over-potentials  $v_1$  and  $v_2$  changed dramatically as the discharging test went on. If this effect is not captured, the modelling accuracy will be significantly reduced.

Note that the battery internal resistance  $R_1$ ,  $R_2$  normally will drop as the battery internal temperature increases, as shown in Fig 7. However, in this fast discharging test, the battery SOC dropped too fast and became the dominant factor to increase the internal resistance. If the battery is heated up at the same SOC, the decrease of  $R_1$ ,  $R_2$  becomes more noticeable. The battery terminal voltage fitting results are shown in Fig 16. As can be seen, the model outputs match very well with the measurements, except for a few error spikes. Generally speaking, the state estimation performance of EKF depends not only on the model accuracy, but also on the choice of EKF parameters. According to the above analysis and experimental results, we conclude that a better model can



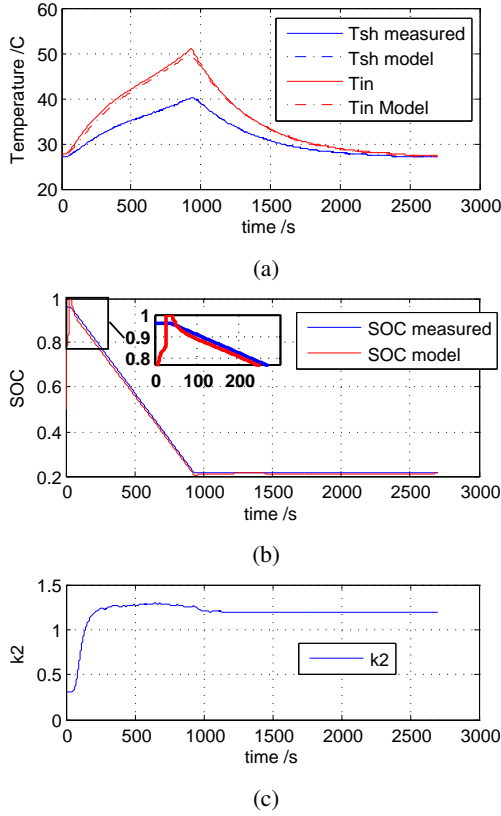


Fig. 14: Kalman filter considering  $T_{in}$  and SOC effect: (a)  $T_{in}$ ,  $T_{sh}$ ; (b)  $soc$ ; (c)  $k_2$

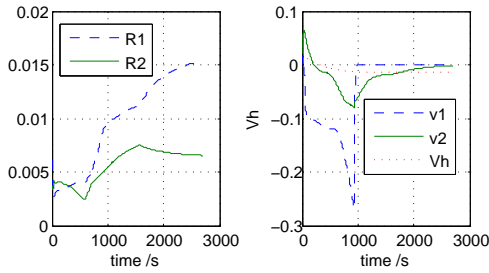


Fig. 15: Kalman filter results considering  $T_{in}$  and SOC effect: electrical submodel parameters  $R_1$ ,  $R_2$  and over-potentials  $v_1$ ,  $v_2$ ,  $V_h$

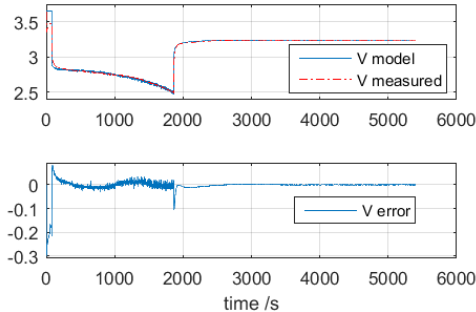


Fig. 16: Kalman filter results considering  $T_{in}$  and SOC effect: battery terminal voltage

significantly improve the state estimation accuracy. This has been achieved through capturing the effect of SOC and  $T_{in}$  on the battery behaviours using the coupled thermoelectric model. It should be noted that some other remedies to improve the internal state estimation accuracy have also been proposed, such as Dual-Kalman Filter method, RLS + EKF, etc. These approaches however can only be more effective with a more accurate model as we have proposed in this paper. It is also worth noting that due to the higher model accuracy by considering the interactions between the battery thermal and electrical behaviours, the EKF parameter tuning used in this study is much easier. To compare these different approaches is beyond the scope of this paper, and it can be a future work.

## VI. CONCLUSIONS

A novel method is proposed in this paper to estimate battery internal temperature and SOC simultaneously. A simplified thermoelectric model is built, including an electrical submodel and a thermal submodel. For the thermal submodel, different methods for calculating the heat generation inside the battery are compared; for the electrical submodel, the effect of battery internal temperature and SOC on the battery electrical behaviours is characterized and captured. The time-varying thermal submodel parameter is also taken into consideration, and a joint EKF is applied to estimate the model states and time-varying model parameter simultaneously. The proposed estimation method is based only on the online measurable signals, e.g., battery voltage, current and shell temperature, and thus can be implemented in real-time. Test data are collected using a LiFePO<sub>4</sub>/C battery. The modelling and internal temperature and SOC estimation results has confirmed the efficacy of the proposed method.

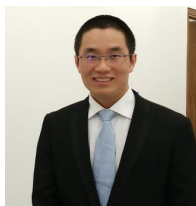
The developed simplified thermoelectric model and internal temperature estimation method proposed in this paper can be used to help design a proper BMS in EVs. Firstly, a simplified model can be used for initial assessment of the BMS design, and the proposed method can be used offline to simulate both the battery internal and surface temperature responses under various load current profiles and working conditions, which can be further used as a guidance for designing the battery thermal management system. Secondly, in terms of online applications, the real-time estimation of battery internal temperature can serve as an indicator or a control objective to prevent dangerous battery operations that may lead to too high battery internal temperature, thus helps to prolong the battery service life and to enhance the battery safe operations, which is a major design consideration for EVs.

Future work to further improve the model accuracy may consider the following three aspects: 1) variations of thermal and electric behaviours between cells within a battery pack; 2) battery ageing and usable capacity reduction with cycling usage; 3) the temperature effect on battery OCV.

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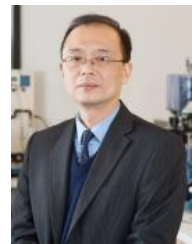
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